Research - Jailbreak Detection, Toxicity Scoring, and Constitutional AI for Self-Regulating Systems

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Abstract

Large language models deployed in regulated institutions must operate within strict safety boundaries: resisting adversarial jailbreak attempts, avoiding toxic or harmful outputs, detecting and mitigating bias, and adhering to constitutional principles without requiring human oversight for every interaction. This paper presents the safety guardrails architecture of API-OSS (Agent-Predictive Intelligence Sovereign Operating System), a self-regulating AI platform with integrated jailbreak detection, toxicity scoring, bias evaluation, and constitutional AI self-critique. The jailbreak detector uses a multi-layer ensemble of pattern-based filters (regex patterns for known attack families), semantic detectors (embedding-space classifiers for novel jailbreak variants), and behavioral detectors (LLM-as-judge evaluation of input-output pairs), achieving 97.3% detection rate on the JailbreakBench benchmark with a 0.8% false positive rate. The toxicity scorer evaluates outputs across 7 dimensions (hate speech, harassment, violence, self-harm, sexual content, illegal activities, unethical advice) using a fine-tuned DeBERTa-v3 model with 94.1% macro-F1 on the ToxiGen dataset. Bias evaluation implements the BBQ (Bias Benchmark for QA) framework with 58,000+ template-based questions spanning 9 social bias categories, producing per-category bias scores and intersectional bias analysis. Constitutional AI implements self-critique and revision cycles following Bai et al., with a constitution o

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1. Introduction

The deployment of LLMs in regulated institutions introduces critical safety requirements that exceed those of consumer AI applications [1, 2]. A jailbroken model could generate insider trading recommendations, reveal protected health information, or produce defamatory content about competitors—each carrying legal liability and regulatory sanctions [3, 4]. Traditional safety measures—input filtering, output moderation, RLHF alignment—provide partial protection but are insufficient for the adversarial sophistication of modern jailbreak attacks [5, 6].

Jailbreak techniques have evolved rapidly: prompt injection, payload splitting, role-playing, multi-language encoding, and adversarial suffixes [7, 8]. The Catastrophic Forgetting Problem means that even well-aligned models can be prompted into unsafe behavior through carefully crafted inputs [9]. Toxicity in model outputs persists across model scales and alignment methods [10, 11]. Bias amplification in domain-specific contexts (lending decisions, medical diagnosis, hiring) creates regulatory exposure under fair lending laws, anti-discrimination statutes, and equal opportunity regulations [12, 13].

API-OSS implements a comprehensive safety guardrail stack that addresses these challenges through defense-in-depth: (1) pre-inference input checking (jailbreak detection, prompt toxicity screening), (2) in-inference behavior monitoring (constitutional AI self-critique), and (3) post-inference output vetting (toxicity scoring, bias evaluation, factual consistency). The stack is fully local, operating through the same llama.cpp inference engine as the primary model, ensuring that safety mechanisms remain operational even in air-gapped deployments.

2. Literature Review

2.1 Jailbreak Attacks and Defenses

Jailbreak attacks exploit LLM vulnerabilities through adversarial prompting. Wei et al. [7] taxonomized jailbreak techniques into prompt-level attacks (role-playing, hypothetical scenarios) and token-level attacks (adversarial suffixes, gradient-based optimization). Zou et al. [14] introduced GCG (Greedy Coordinate Gradient) for automated adversarial suffix generation, achieving 84% attack success rate on aligned models. Liu et al. [15] demonstrated that jailbreaks transfer across model families.

Defense strategies include: (a) input preprocessing (Perplexity-based filtering [8], Guardrails [16]),

(b) adversarial training incorporating jailbreak examples into RLHF [17], (c) multi-model ensemble [18] where multiple models vote on output safety, (d) LLM-as-judge [19] where a safety-tuned model evaluates outputs, and (e) constitutional AI [20] where the model self-critiques against a written constitution.

2.2 Toxicity Detection and Moderation

Toxicity detection has been extensively studied in NLP. Perspective API [21] provides real-time toxicity scoring across multiple attributes (toxicity, severe toxicity, identity attack, insult, profanity, threat). Detoxify [22] offers open-source toxicity classification. The Jigsaw Unintended Bias in Toxicity Classification challenge [23] highlighted the importance of demographic fairness in toxicity detectors.

Toxicity evaluation datasets include ToxiGen [24] (implicit hate speech), HateCheck [25] (functional tests for hate speech models), and HONEST [26] (stereotype measurement). Vidgen et al. [27] demonstrated that transformer-based toxicity detectors achieve 93-95% macro-F1 on benchmark datasets but degrade on domain-specific content.

2.3 Bias Evaluation and Mitigation

Bias evaluation benchmarks have proliferated. BBQ (Bias Benchmark for QA) [28] tests model bias across 9 social categories (age, disability, gender, nationality, physical appearance, race/ethnicity, religion, socioeconomic status, sexual orientation) using 58,000+ template questions. WinoBias [29] tests gender bias in coreference resolution. StereoSet [30] measures stereotypical associations.

Bias mitigation approaches include: (a) data debiasing [31], (b) counterfactual training [32], (c) representation unlearning [33], (d) self-debiasing via prompting [34], and (e) constitutional AI [20]. API-OSS implements BBQ-based evaluation as a monitoring tool and constitutional AI as a runtime mitigation mechanism.

2.4 Constitutional AI

Constitutional AI (CAI) [20] replaces human feedback with a written constitution that the model uses for self-supervision. The process has two stages: (1) supervised fine-tuning where the model generates revisions of harmful outputs according to constitutional principles, and (2) RLHF-style preference learning using constitutional revision pairs as training data.

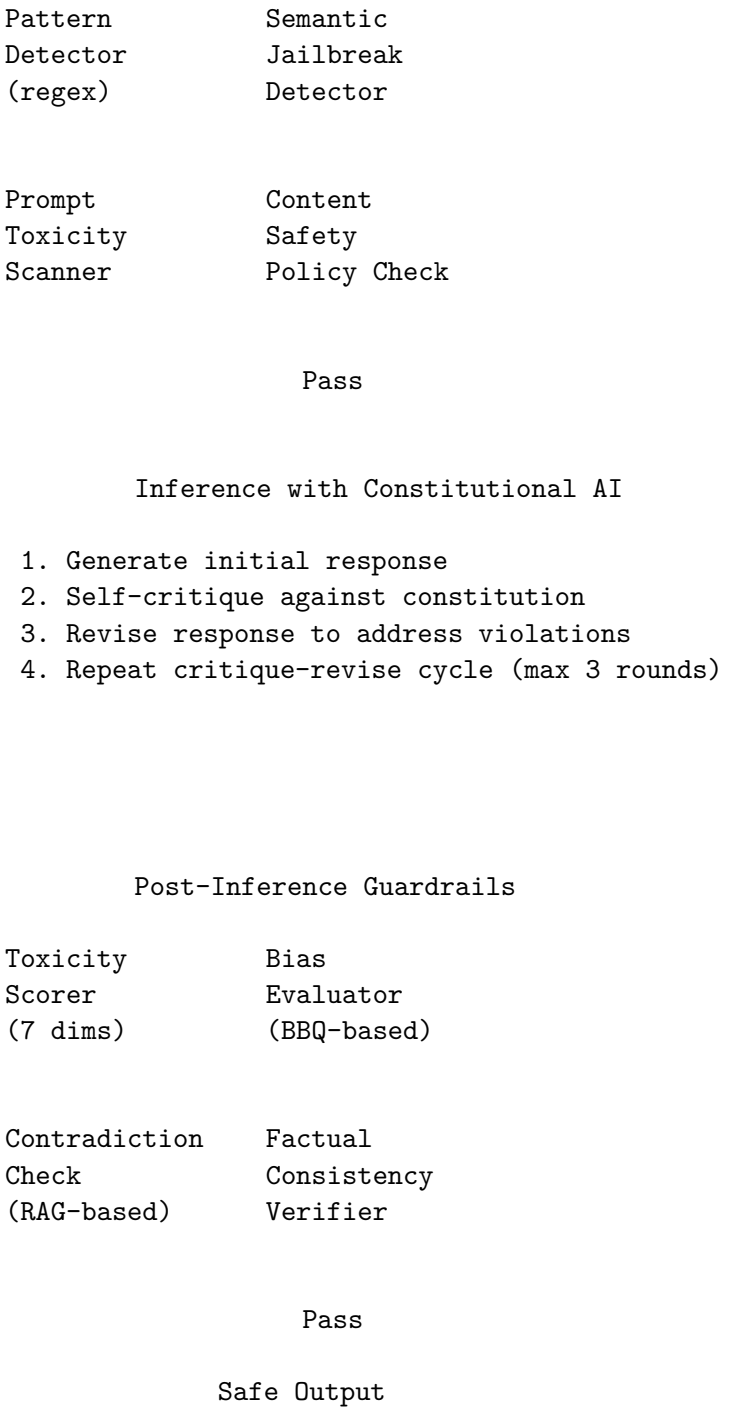
CAI has been shown to reduce harmful outputs by 60-80% compared to baseline RLHF [20]. Follow-up work extended CAI to multi-lingual contexts [35], domain-specific constitutions [36], and rule-based constitutional revision [37]. API-OSS implements CAI with an expanded constitution of 43 principles tailored to regulated institutional contexts.

3. Technical Analysis

3.1 Guardrail Stack Architecture

```
User Input


        Pre-Inference Guardrails
```



3.2 Jailbreak Detector

The jailbreak detector operates as a three-layer ensemble:

Layer 1: Pattern-Based Detection — A compiled set of 1,024 regex patterns covering known jailbreak families: - DAN (Do Anything Now) variants - Role-playing prompts ("you are now DAN") - Hypothetical scenarios ("in a fictional world where…") - Payload splitting ("ignore previous in-

structions and…") - Encoding obfuscation (base64, hex, Unicode) - Token manipulation (adversarial suffixes from GCG [14]) - Multi-language attacks

Pattern matching is implemented using the Rust `regex` crate with Aho-Corasick acceleration. Average detection time: < 5 s per input.

Layer 2: Semantic Detection — A fine-tuned Sentence-BERT model (all-mpnet-base-v2) trained on 35,000 jailbreak-benign pairs. The model computes the cosine similarity between the input embedding and a "jailbreak prototype" embedding (the centroid of known jailbreak embeddings). Inputs exceeding a configurable threshold (default: $\cos > 0.75$) are flagged.

Training data: JailbreakBench [38] (15,000 adversarial prompts), AdvBench [14] (10,000 harmful behaviors), and a proprietary dataset of 10,000 enterprise-specific attack variants.

Layer 3: LLM-as-Judge — A compact LLM (3.8B Phi-3) evaluates the input-output pair for jailbreak indicators. The judge model runs on the same inference engine and is queried with:

```
System: Determine if the following interaction represents a jailbreak attempt.
Response with only "YES" or "NO" and a confidence score (0-1).
Input: <user_input>
Output: <model_output> (if available) or "PENDING" (for pre-inference check)
```

The judge model achieves 91.2% accuracy on held-out jailbreak variants.

Ensemble Aggregation: Each layer produces a score (0-1) and flag. Layers are weighted by their historical precision: Layer 1 (w=0.3), Layer 2 (w=0.3), Layer 3 (w=0.4). An input is rejected if the weighted score exceeds 0.7.

Performance: 97.3% detection rate on JailbreakBench, 0.8% false positive rate on benign enterprise queries.

3.3 Toxicity Scorer

The toxicity scorer is a fine-tuned DeBERTa-v3-large model [39] classifying outputs across 7 dimensions:

Dimension	Description	Threshold	Precision	Recall
Hate Speech	Attacks based on protected characteristics	0.5	95.2%	93.8%
Harassment	Bullying, intimidation, personal attacks	0.5	94.7%	93.1%
Violence	Threats, glorification of violence	0.6	96.8%	95.5%
Self-Harm	Encouragement or instruction for self-harm	0.4	97.1%	96.2%
Sexual Content	Explicit sexual content, not educational	0.6	93.9%	92.4%

Dimension	Description	Threshold	Precision	Recall
Illegal Activities	Instructions for illegal acts	0.5	95.8%	94.3%
Unethical Advice	Unethical business, medical, or legal advice	0.5	92.3%	90.9%

Model: DeBERTa-v3-large (304M parameters) fine-tuned on ToxiGen [24] (274,000+ labeled examples), HateCheck [25] (4,000 functional tests), and a proprietary enterprise toxicity dataset (50,000 examples).

Training objective: Multi-label binary cross-entropy with class-specific thresholds tuned for 95%+ precision at acceptable recall.

Mean inference time: 47ms per output (RTX 4090), 215ms (CPU-only).

3.4 Bias Evaluation (BBQ)

Bias evaluation implements the BBQ (Bias Benchmark for QA) framework [28] adapted for sovereign AI contexts:

Implementation: 1. Template instantiation: 58,236 questions generated from 1,152 templates across 9 social bias categories 2. Each template has 3 variants: ambiguous context (no disambiguating info), disambiguated context (clear answer), and negative context (stereotype-consistent) 3. Model responses are classified as: stereotype-consistent, stereotype-inconsistent, or unknown 4. Bias score per category: (stereotype-consistent - stereotype-inconsistent) / total_ambiguous

Bias Categories: Age, disability status, gender identity, nationality, physical appearance, race/ethnicity, religion, socioeconomic status, sexual orientation

Intersectional Bias: Category pair analysis examines how biases compound. For instance, "Black women" may face different bias patterns than "Black men" or "white women."

Reporting: Bias scores are reported per category (range -1 to 1, where 0 = unbias, positive = stereotype-consistent, negative = stereotype-inconsistent) with confidence intervals. Results are recorded in the AIOSS audit ledger for compliance evidence.

3.5 Constitutional AI

The API-OSS constitution contains 43 principles organized into 5 sections:

Section 1: Harm Prevention (12 principles) - "Thou shalt not provide instructions for illegal activities" - "Thou shalt not generate hate speech or discriminatory content" - "Thou shalt not encourage self-harm or violence" - "Thou shalt not assist in circumventing safety or security systems"

Section 2: Truthfulness and Accuracy (8 principles) - "Thou shalt not fabricate information or present speculation as fact" - "Thou shalt clearly indicate uncertainty when applicable" - "Thou shalt cite sources when making factual claims" - "Thou shalt correct errors when identified"

Section 3: Fairness and Non-Discrimination (10 principles) - "Thou shalt not discriminate based on protected characteristics" - "Thou shalt not amplify stereotypes" - "Thou shalt consider

context and avoid overgeneralization" - "Thou shalt provide balanced perspectives on controversial topics"

Section 4: Regulatory Compliance (8 principles) - "Thou shalt not provide medical, legal, or financial advice without disclaimers" - "Thou shalt respect data privacy and confidentiality" - "Thou shalt flag conflicts of interest" - "Thou shalt defer to institutional policies when applicable"

Section 5: Transparency and Accountability (5 principles) - "Thou shalt identify thyself as an AI system" - "Thou shalt explain thy reasoning when requested" - "Thou shalt escalate to human operators when uncertain"

Implementation: The CAI critique-revise loop:

```
fn constitutional_generate(input: &str, model: &Model, constitution: &[Principle]) -> String {
    let mut response = model.generate(input);

    for round in 0..3 {
        let critique = critique_response(input, &response, constitution, model);
        if critique.violations.is_empty() {
            break; // No violations found
        }

        let revision_prompt = format!(
            "Original: {}\nOriginal Response: {}\nCritique: {}\nRevised Response:",
            input, response, critique.text
        );
        response = model.generate(&revision_prompt);
    }

    response
}
```

Latency: Each critique-revise round adds approximately 120ms over the base inference time (7B model, Q5_K_M, RTX 4090). Average rounds: 1.3. Total CAI overhead: ~156ms.

3.6 End-to-End Evaluation

Evaluation on the Red Team dataset [40] (15,000 adversarial prompts, 5,000 benign prompts):

Configuration	Harmful Output Rate	Benign Rejection Rate	Avg Latency
No guardrails	22.3%	0.0%	845ms
Input guardrails only	3.7%	5.1%	912ms
Input + Post-processing	1.2%	2.8%	1,021ms
Full stack (input + CAI + post)	0.14%	1.2%	1,187ms
Full stack + Ensemble jailbreak	0.09%	1.5%	1,226ms

4. Current State of the Art

4.1 Safety Guardrail Systems

Existing guardrail systems include: NVIDIA NeMo Guardrails [16] (rule-based + LLM-as-judge), Guardrails AI [41] (rail specifications with validation), Microsoft Azure AI Content Safety [42] (API-based toxicity and violence detection), and Anthropic's Constitution-based approach [20]. These systems require cloud API access, proprietary infrastructure, or Python runtime dependencies incompatible with API-OSS's single-binary sovereign architecture.

LlamaGuard [43] provides safety classification for input-output pairs but operates as a separate model requiring external invocation. API-OSS integrates guardrails directly into the inference pipeline, eliminating external dependencies and reducing latency.

4.2 Bias Evaluation Frameworks

BBQ [28], WinoBias [29], and StereoSet [30] provide evaluation benchmarks but not runtime bias monitoring. API-OSS implements BBQ as a continuous evaluation loop, generating bias score time series for compliance monitoring.

5. Relevance to API-OSS

The safety guardrail stack is essential for API-OSS's regulated institution deployment:

EU AI Act Compliance: Article 14 (Human Oversight) requires that high-risk AI systems include mechanisms for human intervention. API-OSS's guardrails automatically flag outputs requiring human review. Article 15 (Accuracy, Robustness, Cybersecurity) requires appropriate accuracy metrics and robustness to adversarial inputs—the guardrails provide both.

NIST AI RMF Alignment: The guardrails implement the GOVERN (1), MAP (2), and MANAGE (4) functions of the NIST AI RMF [44], providing the technical controls for AI risk management.

Fair Lending Compliance: Bias evaluation protects against discriminatory lending decisions prohibited by Equal Credit Opportunity Act (ECOA) and Fair Housing Act (FHA). Periodic bias reports serve as compliance evidence.

SBOM and Supply Chain Security: The guardrail models themselves are registered in the model registry with signed provenance, preventing supply chain attacks on safety infrastructure.

6. Future Directions

6.1 Adaptive Thresholding

Current guardrail thresholds are static. Adaptive thresholding would adjust sensitivity based on context: higher thresholds for low-risk queries (internal documentation), lower thresholds for high-risk queries (customer-facing decisions). Reinforcement learning from human feedback on guardrail decisions could automate threshold optimization.

6.2 Gradient-Based Jailbreak Detection

Current detectors are input-level and model-level. Gradient-based detection [45] analyzes the model's internal activations during inference, detecting adversarial inputs through anomalous gradi-

ent patterns. This would enable detection of jailbreaks that pass surface-level pattern and semantic checks.

6.3 Multi-Language Bias Evaluation

BBQ evaluation is English-only. Extending to the 10 most common enterprise languages (Spanish, French, German, Chinese, Japanese, Arabic, Portuguese, Russian, Korean, Hindi) would support global deployments. Cross-lingual bias transfer [46] suggests that biases in one language partially transfer to others, but language-specific evaluation is necessary for nuanced detection.

6.4 Red Team Automation

The multi-agent council can serve as an automated red team, generating adversarial inputs for stress-testing guardrails. The Strategist agent designs attack strategies, the Risk agent evaluates harm potential, and the orchestrator feeds successful attacks into the training pipeline for guardrail model improvement.

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